EGU26-2056, updated on 13 Jun 2026
https://doi.org/10.5194/egusphere-egu26-2056
EGU General Assembly 2026

An NWP-Free, Observation-Driven Deep Learning Approach to Heavy-Rainfall Nowcasting Beyond the Three-Hour Limit

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Quasi-stationary convective bands over Kyushu, Japan, frequently trigger rainy-season disasters, and hours with ≥50 mm h^{-1} rainfall are increasing. Yet skillful nowcasts beyond 3 h remain limited. This study presents FlowsNet, an observation-based multi-sensor fusion model that learns directly from radar/rain gauge-analyzed precipitation, surface variables from ground stations, geostationary satellite imagery, and satellite-derived precipitation context. The model targets category-4 (C4; ≥50 mm h^{-1}) rainfall and incorporates two attention mechanisms: a channel-wise module that weights informative modalities and a spatial module that aligns features with banded structures at multi-hour leads. Training uses a tail-aware ordinal loss that couples focal reweighting with Earth Mover's Distance to highlight rare extremes. FlowsNet maintains a non-zero C4 Critical Success Index through 6 h. From 4 to 6 h, it matches or exceeds the Japan Meteorological Agency's very-short-range forecast, and it outperforms a leading extrapolation method and current deep-learning nowcasters. Case studies show preserved band geometry and corridor placement at long lead over complex terrain. Ablation experiments identify satellite water-vapor context and near-surface humidity as key for long-lead C4 prediction; combining satellite context with surface observations stabilizes placement and reduces false alarms. By avoiding numerical weather prediction model state and objective analyses/reanalyzes, the approach reduces latency and hardware demand, improves portability and resilience when model cycles degrade, and offers a practical route to earlier and more transferable warnings for extreme rainfall events.